Transient Stability Assessment Using Artificial Neural Networks

by

Abdul-Aziz Mohammed Al-Shams

A Thesis Presented to the

FACULTY OF THE COLLEGE OF GRADUATE STUDIES

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS

DHAHRAN, SAUDI ARABIA

In Partial Fulfillment of the
Requirements for the Degree of

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In

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This thesis written by A. M. Al-Shams under the direction of his Thesis Advisor and approved by Thesis committee, has been presented to and accepted by the Dean of the college of Graduate Studies, in partial fulfillment of the requirements for the degree of MASTER OF SCIENCE IN ELECTRICAL ENGINEERING.

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﴿ ربِ ارحمهما كما ربياني صغيراً ﴾

Dedicated to my parents.

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التخصص:	هندسة كهربائية
تاريخ الدرجة:	محرم ١٤١٦ هـ

تقدّم هذه الرُسالة دراسة لمدى ملائمة الشبكات العصبية الصناعية لتقييم التوزان اللحظي لأنظمة القدرة . تم في هذه الرسالة تطوير شبكات عصبية صناعية لتؤلف الإرتباط المعقّد الذي ينقل متغيرات عمل النظام ومواقع الإلتماس إلى زمن المقاصة الحرجة (CCT). لقد تم تدريب هذه الشبكات العصبية الإصطناعية باستخدام طريقة الإمتداد الرجعي وطريقة المساحة المتساوية الموسّعة (EEAC) للحصول على قيم زمن المقاصة الحرجة (CCT) . قصد في هذه الرسالة تجنّب أي تحفظات أو قيود على التغيرات في الأعمال والتركيبات . النتائج مماثلة بشكل عام لتلك التي نشرها آخرون حديثاً.

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THESIS ABSTRACT

Name of student:	Al-Shams, Abdul Aziz Mohammed
Title of study:	Transient Stability Assessment Using Artificial Neural Networks
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This thesis presents a study of the feasibility of using Artificial Neural Networks for Transient Stability Assessment of power systems. In this research, Artificial Neural Networks have been developed to synthesize the complex mappings that carry the power system's operating variables and faults locations into the Critical Fault Clearing Times. Training of the Artificial Neural Networks has been achieved through the method of backpropagation. The Critical Fault Clearing Time values are obtained by the Extended Equal Area Criterion method and are used for training. In this work, an attempt was made to avoid the restrictions on load and topology variations. The results obtained are in general agreement with those reported recently by other researchers.

MASTER OF SCIENCE DEGREE

KING FAHD UNIVERSITY OF PETROLEUM AND MINERALS

Dhahran, Saudi Arabia

CHAPTER I

INTRODUCTION

1.1 The Stability Problem

Transient stability studies aim at evaluating whether or not a credible disturbance could lead to the instability of the power system under analysis. Stability studies are subdivided, depending on the nature and the order of magnitude of the disturbance, into three sub-studies: transient, dynamic, and steady state stability studies. Transient stability studies are aimed at determining whether or not the system will maintain synchronism following major disturbances including transmission system faults, sudden load changes, loss of generating units, or line switching. [1]

The power system model for stability analysis can be, in general, written as [2]:

$$\frac{dx}{dt} = f(x, y) \tag{1.1a}$$

$$f(x, y) = 0 \tag{1.1b}$$

The differential equations (1.1a) describe the dynamics of the machines and their associated control systems; the nonlinear algebraic equations (1.1b) state the network steady state and the interface connecting the machines with the network. If the classical model for generators is used (the generator is represented by a constant voltage source behind the direct axis transient reactance) and the network is modeled by the admittance matrix, then the resulting simplified model is as follows [2]:

$$M_i \frac{d^2\delta_i}{dt^2} + D_i \frac{d\delta_i}{dt} = P_{mi} - P_{ei} \tag{1.2a}$$

$$I = YV \tag{1.2b}$$

Where δ_i is the phase angle of i-th generator's internal voltage, M_i is the i-th machine inertial constant, D_i is the i-th machine damping constant, P_{mi} is the mechanical power fed to the i-th machine and P_{ei} is the electrical power delivered by the i-th machine to the network, I is the bus injected current vector, V is the bus voltage vector and Y is the network admittance matrix.

The conventional power system stability study computes and analyzes, based on the previous equations, the system response to a sequence of events (or disturbances). A variety of computational procedures and techniques have been applied in the field of power system stability assessment including numerical integration methods, direct methods, probabilistic methods, pattern recognition methods and expert systems. These methods are briefly described in CHAPTER II.

All stability studies and methods aim at determining whether or not the rotors of the system's machines being perturbed return to constant speed operation. In the case of transmission system faults, as well a other disturbances, the longer the period of the fault, the more likely the system will loose synchronism. The Critical Fault Clearing Time (CCT) is the longest fault duration the system withstands while maintaining synchronism. It is used as a measure of the stability of a power system following a disturbance. Thus, the critical fault clearing time is considered as one of the parameters of paramount importance.

1.2 Thesis Objective

Fast and efficient method for transient stability analysis has been sought due to the increase in size and complexity of power systems owing to continuously growing power demand. The critical fault clearing time is used as a measure of relative stability for the system under the impact of a given fault. However, the evaluation of the critical fault clearing time is computationally involved and time consuming. The objective of this thesis is to study the feasibility of using artificial neural networks to synthesize the complex mappings that carry the power system's operating variables and fault locations into the single valued space of the critical fault clearing times.

1.3 Scope of the Thesis

This thesis presents artificial neural networks as a fast mean for computing the critical clearing time of a power system. In the artificial neural networks the system operating variables such as generator output power and load demand and others may be used as inputs. Training of the artificial neural networks will be based on values of the critical fault clearing time computed using the extended equal area criterion method. The extended equal area criterion method is presented in CHAPTER V.

The thesis is organized as follows:

A brief review of existing transient stability assessment approaches is presented in CHAPTER II. CHAPTER III is an overview of artificial neural networks' concepts, operation and training. CHAPTER IV is a brief literature survey on previous research work in using artificial neural networks as tools for estimating the critical clearing time. Computing the critical clearing time using the extended equal area criterion method is presented in CHAPTER V. The applications and results of using artificial neural networks to estimate the critical clearing time of three-machine-nine-bus system is presented in CHAPTER VI. CHAPTER VII presents conclusions and recommendations for future work in this field.

CHAPTER II

Transient Stability Solution Techniques

A variety of methods for transient stability assessment has been proposed in the power systems literature. These methods can be broadly divided into the following categories:

- Numerical integration,
- Direct methods,
- Probabilistic methods,
- Pattern recognition methods, and
- Expert systems.

A brief description of each method is presented below.

2.1 Numerical Integration (Time Domain Simulation)

The system, which is described by a set of first order algebraic and differential equations, is simulated, step by step, for the entire study period including the during-fault period and post-fault period. The most commonly used numerical integration algorithms are the Runge-Kutta predictor and the predictor corrector methods. The simulation methods are the most reliable, in the sense of providing exact answers related to the stability of the system. Considering the constraints of real time operations, the drawbacks of these methods can be summarized as follows:

1. Each contingency must be analyzed separately,

2. Stability limits, power limits and critical clearing time, are obtained by separate trials, and

3. Smaller time-step intervals are necessary in order to ensure the accuracy and the numerical stability of the solution method.

Therefore, the application of these methods is time consuming and as such are not suitable for on-line stability assessment. [1]

2.2 Direct Methods

A number of direct methods have been presented in the literature [3-6]. The following is a summary of major classes of these methods.

a) The Second Method of Lyapunov

These methods, basically, eliminate the step-by-step integration of the post-fault system equations by the stability criterion. The principle of transient stability analysis is based on the second method of Lyapunov. It is based on the construction of Lyapunov functions, mostly an energy like function, and then finding the region of stability of the Stable Equilibrium Point (SEP) associated with this function. The value of a suitable designed Lyapunov function V is calculated at the instant of the last switching in the system and compared to the previously determined critical value, V_{cr}. The system is stable if the value of V is smaller than V_{cr}. Unfortunately, if the value of V is greater than V_{cr}, no conclusion can be drawn on whether the system is stable or not.

Research on the theoretical and practical issues related to the application of Lyapunov theory in stability evaluation pointed out unresolved problems and drawbacks. These include:

1. Simplified Classical machine models are used in the construction of Lyapunov functions. The generated voltage of the generator and the mechanical input are assumed constant during the transient period.

2. Integration of the fault-on system equations is required in order to obtain the post-fault initial conditions and the critical clearing time.

3. Most of the reported investigations are based on neglecting transfer conductances, despite their role in reduced networks. This can be corrected, at the expense of the increased computation complexity.

4. The criterion is a *sufficient* one (the main source of its conservativeness) and the (in)stability cannot be determined in case the operating point is outside the estimated stability region.

b) The Extended Equal Area Criterion

The Extended Equal Area Criterion (EEAC) method is a simple method that has been proposed as a tool for fast transient stability assessment [7-11]. This method is based on replacing the multimachine system by two groups of machines: a group consisting of the critical cluster and the group of remaining machines. The two groups are then represented by two equivalent machines. The equivalent machines are reduced to a One-Machine-Infinite-Bus (OMIB) system. The stability problem is thus reduced to a sole algebraic equation, devised from the well-known equal area criterion. The extended equal area criterion method will be used, in this research, for the computation of the critical fault clearing time (CCT) of a power system.

c) The Transient Energy Function

The principal of the Transient Energy Function (TEF) method is based on analytical formula of the transient kinetic and potential energy of the post-contingency system [12-19]. The Transient Energy Function (TEF) is defined as an integral of the instantaneous real power mismatch between the electrical and mechanical power at generator nodes. For transient stability assessment, the critical value of the TEF, which corresponds to the controlling Unstable Equilibrium Point (UEP), must be evaluated. In fact, the main drawback of the TEF method is the mathematical difficulty involved in computing the controlling UEP. The system is stable in case the TEF at the end of the disturbance is smaller than the critical value of the TEF. Otherwise, the system is not stable.

2.3 Pattern Recognition

Pattern recognition in transient stability assessment is aimed at minimizing the computation requirement. The classical methodology of pattern recognition consists of defining an 'input' pattern vector. This vector contains all parameters, variables and/or topologies that have significant impact on the system performance (stability in transient stability studies). A training set is obtained by evaluating the input vector at many representative operation conditions. Then a process of dimension reduction , called feature extraction, is performed to identify significant, and hopefully, uncorrelated set of components. The final step is to determine the classification function that determines whether or not a given input pattern corresponds to a stable case. [20-22]

2.4 *Expert Systems*

An Expert System captures human knowledge in a narrow specific domain in a machine useable form. It utilizes this knowledge to provide decision support at a level comparable to human expert and capable of justifying its reasoning. An Expert System consists of three basic elements: knowledge base, inference engine, and human-machine interface. The knowledge base contains facts and heuristics about some specialized knowledge domain. The inference engines carry out interpretations (reasoning) and provides conclusions and recommendations. [23] An Expert system separates the inference mechanisms from the domain specific knowledge. A variety of knowledge structures can be used by an Expert System, including: production rules, frames and objects to represent the knowledge of the Expert System. [24]

Recently a number of research investigation reported on the use of Expert Systems for transient stability assessment [25-28]. In fact, transient stability assessment is considered the most-needed application area for Expert Systems. Expert systems, for transient stability assessment, can be developed to identify imminent disturbances and evaluate their impact on the system performance. Also, Expert Systems can be used in determining proper preventive actions to be taken if an operating condition is likely to become sever.

This thesis deals with application of Artificial Neural Networks for Transient Stability Assessment. Chapter III presents an overview of the basis of Artificial Neural Networks.

CHAPTER III

ARTIFICIAL NEURAL NETWORKS

3.1 Introduction

The recent applications of Artificial Neural Networks (ANNs) revealed that they have great potentials in overcoming difficult data-processing and data-interpretation tasks. Artificial Neural Networks resemble human brain cells and their interconnections. Such networks have exceptional pattern-recognition and learning capabilities. This chapter presents an overview of the features of the Artificial Neural Networks and their applications.

3.2 Mechanism and Operation

A neural network is an information processing system that is non-algorithmic, non-digital, and intensely parallel. It consists of a number of simple highly interconnected processors known as neurons that are analogous of the brain biological neural cells. These neurons are connected by a large number of weighted links, over which signals can pass. Each neuron receives many signals over its incoming connections. However, it never produces more than a single outgoing response that is transmitted over its outgoing connection. The outgoing connection terminates at different destinations: incoming connections of some other neurons or outside the neural network representing its overall response.

3.3 The neuron

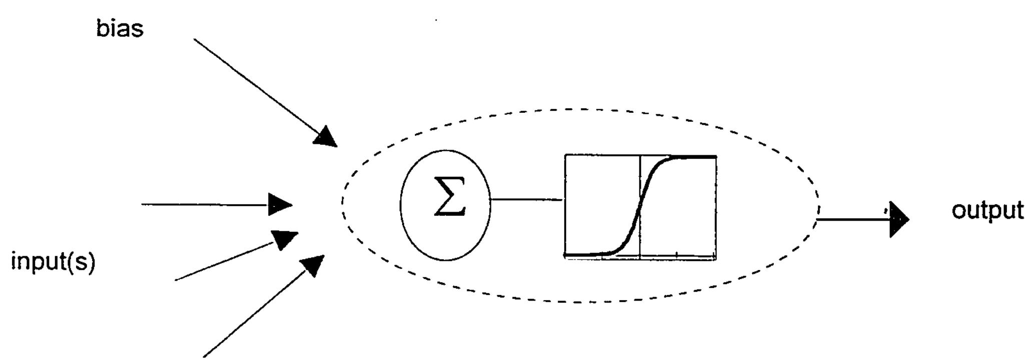

Figure 3.1 Typical neuron

A neuron is a simple processor. A typical neuron is shown in figure (3.1). The neuron receives inputs and translates these inputs into an output response. The inputs' signals are multiplied with their links' weights. The sum of the weighted inputs is biased and passed through an activation function that produces the final neuron's response. One of the most popular activation functions used in neural networks is the sigmoid (S-shaped) function, shown in figure (3.2).

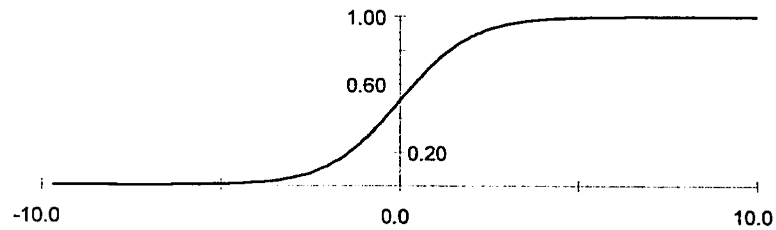

Figure 3.2 Plot of the sigmoid function

This type of neurons determines its output in the following fashion. First, it computes its net, weighted input:

$$net = \sum_{j} w_j O_j \tag{3.1}$$

Where O_j is the jth input signal and w_j is the jth neuron's link weight.

Next, the neuron net is biased and passed through the activation function. The neuron output is given by:

$$f(net) = \frac{1}{1 + e^{-(net + w_0)}} \tag{3.2}$$

Where w_0 is the neuron's bias parameter.

The sigmoidal function has a convenient property that its derivative can be expressed in terms of the function itself, being merely:

$$\frac{d}{dt}(f(net)) = f(net)(1 - f(net)) \tag{3.3}$$

3.4 Multilayer backpropagation Artificial Neural Networks

The most popular type of Artificial Neural Networks (ANNs) is a layered-node arrangement known as the Backpropagation (BP) artificial network shown in figure (3.3).

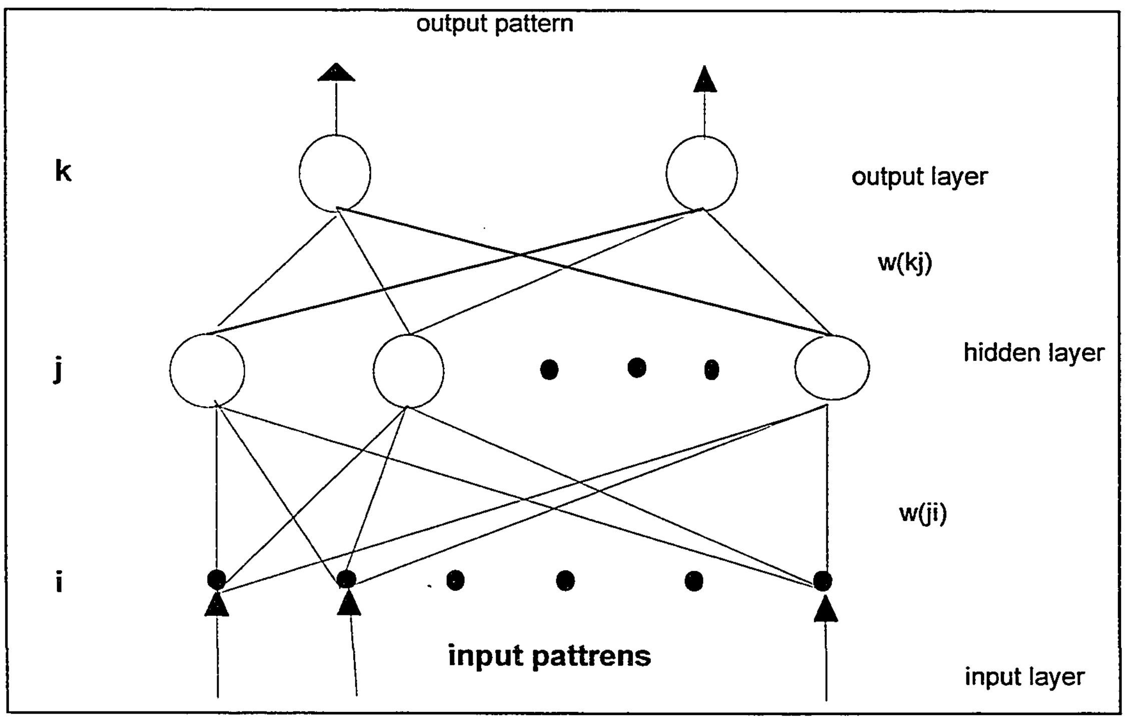

Figure 3.3 Backpropagation Artificial Neural Network

This type of Artificial Neural Networks has an input layer, one or more hidden layer(s), and an output layer. The layers are interconnected by the pre-trained weight links. The hidden layers and the output layer consist of a number of neurons. The input layer receives the input signals and passes its neurons outputs to the immediate hidden layer. The outputs of this hidden layer are forwarded to the next layer. The signals are forwarded in this manner up to the output layer that computes the final output(s) response of the neural network.

3.5 Training a neural network

A neural network is trained to solve a given problem by finding a set of weights and biases representing the problem's solution. Learning is achieved by systematically modifying the weights and biases of the neural network in order to improve the network's output response performance to acceptable levels. Training can take place in three distinct ways: supervised training (most common), graded training, and unsupervised training.

In the supervised training technique, the network is provided with series of input patterns and their corresponding desired output pattern. The learning law for such networks computes an error function by comparing the actual neural network's output with the desired output pattern. The error function values obtained are used to update the neural network weights.

The graded training technique, also called reinforcement training, is similar to the supervised training except that the exact desired output response is not provided. Different graded schemes vary from giving merely a brief massage such as 'you succeeded' or 'you failed' to more informative massage such as 'too high' or 'too low' performance feed back.

Unsupervised training, or self-organization, presents only a series of input patterns to the neural network without any information or feedback about its performance levels. This type of training technique is commonly used for categorization or statistical modeling applications, since the network's specific responses can not be predetermined by the designer.

The backpropagation Artificial Neural Networks use the network output for training based on the least squared error criterion. In fact, backpropagation Artificial Neural Networks are usually the first choice of networks developers. The backpropagation Artificial Neural Networks are simple to implement and can solve wide range of problems correctly. In this research, backpropagation networks will be adapted to provide the critical fault clearing time (CCT) of a power system. In the following section, the training of backpropagation networks will be explored.

3.6 Error backpropagation Training method

Training of the feedforward Artificial Neural Networks can be accomplished by means of the Error Backpropagation method. This method is summarized in the following. An input pattern is fed into the input layer and forwarded to the hidden and output layers. The actual neural output pattern is compared to the desired one obtaining the error. The error is propagated backwards through the network adjusting the weights of its layers. Adjustments of the weights are made first by modifying the hidden-to-output weights and computing the error signals at the output layer. Then, these terms are propagated backwards to the hidden layer to compute the error signals that are used to update the input-to-hidden weights.

Initially, the weights of the network are assigned random values between (-1) and (1). Then, a pair of input pattern and its corresponding output pattern is presented to the neural network. This output is compared with the neural network output pattern as computed based on the ANN current weights. The error at the kth neuron's output is:

$$e_k = t_k - o_k \tag{3.4}$$

Where t_k and o_k are the desired and actual output of the kth output neuron respectively.

The training process is based on minimizing a cost function defined as:

$$E = \frac{1}{2} \sum_k (t_k - o_k)^2 \tag{3.5}$$

$$E = \frac{1}{2} \sum_k e_k^2 \tag{3.6}$$

The gradient descent procedure is a simple technique that can be used to minimize the previous function. The gradient descent rule specifies the change in a given connection weight as [30]:

$$\Delta w_{kj} = \eta \; \delta_k \; o_j \tag{3.7}$$

Where η is the learning rate parameter and δ_k at an output neuron k is given by:

$$\delta_k = (t_k - o_k) o_k (1 - o_k) \tag{3.8}$$

and δ_j at an arbitrarily hidden neuron j is given by:

$$\delta_j = o_j (1 - o_j) \sum_k \delta_j w_{kj} \tag{3.9}$$

Adding Momentum Term

Better convergence of a backpropagation network can be achieved by adding a momentum term to the changes in the network weights. This is implemented by redefining the change in the weights as follows:

$$\Delta w_{kj} = \eta \ \delta_k \ o_j + \alpha \ \Delta w_{kj}^{previous} \tag{3.10}$$

Where

α is the momentum constant that has a value between 0.0 and 1.0.

$\Delta w_{kj}^{previous}$ is the previous change in w_{k}.

Adding the momentum term tends to keep the network weights moving in the same direction unless nudged forcefully in a different direction. Momentum term is similar to the physical momentum of a sled sliding down a hill, the change in the network weights has a term that tends to keep the weights moving so it does not get trapped easily in a local minimum.

3.7 Advantages of Artificial Neural Networks

Research on the application of Artificial Neural Networks have reported a number of advantages:

Capability of synthesizing complex and transparent mapping: an artificial neural network can grasp and synthesize complex and transparent mappings that are difficult to be stated in straightforward mathematical expressions.

Rapidity: Because of their parallel mechanism, once an artificial neural network is trained, it solves the mapping problems much faster than conventional methods and other artificial intelligent methods.

Adaptivity: Artificial Neural Networks can be trained on-line by its error performance. So, Artificial Neural Networks can adapt to new environment easily.

Less memory requirement: Only the weights of the trained Artificial Neural Networks are needed to be stored. [31]

3.8 Applications of Artificial Neural Networks in electrical power engineering

Artificial Neural Networks have been suggested for various power system applications. Practical implementations have been documented in areas such as state estimation, economical load dispatching [31], security and contingency analysis [32], machine modeling and identification [33,34], alarm processing, load forecasting [35], and load estimation and var control [36]. CHAPTER FOUR presents a summary of recent applications of artificial neural network in transient stability assessment.

CHAPTER IV

APPLICATIONS OF ARTIFICIAL NEURAL NETWORKS ON TRANSIENT STABILITY:

A LITERATURE REVIEW

In recent years, Artificial Neural Networks (ANNs) have attracted considerable attention as candidates for fast assessment of transient stability. Applications of artificial neural networks, in this field , as reported in the literature are reviewed in the following.

In February 1989, Dejan and Pao have published a paper on the application of artificial neural networks for computing the critical fault clearing time (CCT) of a power system [30]. They have developed an Artificial Neural Network (ANN) that computes the critical fault clearing time (CCT) of four machines six buses system. The hidden layer of this Artificial Neural Network has six neurons while its output layers consist of a single neuron. The inputs to the Artificial Neural Network (ANN) includes functions of the generators angles relative to the Inertial center of angles, the mechanical powers and the electrical powers computed at the fault initiation. They have limited the training set patterns to specific topologies. The loading conditions were limited to 15 for each topology. The trained Artificial Neural Network (ANN) provides critical fault clearing time (CCT) with acceptable accuracy. The success of this work was degraded by the limited training set patterns. However, it has brought into attention the feasibility of using the Artificial Neural Network (ANN) as a tool for computing the critical fault clearing time (CCT).

In May 1991, Park and El-Sharkawi published a paper on the application of Artificial Neural Network for security assessment of power systems [32]. The proposed Artificial Neural Network (ANN) technique is described by the following procedure:

- Identify the contingency parameters: The parameter(s), variable(s) and/or topologies which have impact on power security are specified. These parameters are used as inputs to the Artificial Neural Network (ANN).

- Establish off-line security contours: security contours of the system for some values of each contingency parameters are obtained by assessing the eigenvalues of the entire power system.

- Training the Artificial Neural Network (ANN): The Artificial Neural Network (ANN) comprehends the security contours, established in the previous step, during the training process. The Artificial Neural Network (ANN) is trained, only, with selected points that represent stable and unstable operations. The input to the Artificial Neural

Network (ANN) contains the contingency parameters. The output of the Artificial Neural Network (ANN) represents the status of the system stability.

- Test the Artificial Neural Network (ANN): the Artificial Neural Network (ANN) is tested, after training, at other values not necessarily part of the training set.

The proposed Artificial Neural Network (ANN) has a scale problem which may lead to severe difficulties in using it as an on-line aid for Transient Stability Assessment (TSA) of Large-scale systems [32].

In December 1991, Hsu and Chen have developed an Artificial Neural Network for the tuning of Power System Stabilizers (PSS). The inputs to the Artificial Neural Network consist of the generator power (P) and the power factor (PF) which characterize the loading conditions of the generator. The Artificial Neural Network is trained to provide the PSS gain settings based on off-line computed setting values. The training sets consist of different values of the power and the power factor. Simulation results for a synchronous generator subject to three phase fault indicates that the gain settings provided by the trained Artificial Neural Network (ANN) can offer good dynamic performance over a wide range of operating conditions. [38]

In September 1992, Djukanovic and Sobajic presented an Artificial Neural Network (ANN) to be used as a tool for fast stabilization of multi-machine systems. The proposed approach utilizes the generator shedding as an effective control means for improving the dynamic performance of faulted power systems and preventing instabilities. The sensitivity of the Transient Energy Function (TEF) with respect to change in the amount of dropped generation is used in training the Artificial Neural Network (ANN) to assess the critical amount of generation shedding required to prevent the loss of synchronism. The trained Artificial Neural Network (ANN), provided with the fault information, is used to determine the amount of generation to be used. [39]

In September 1994, Nishiura, Shsawa, Arai and Takeno have released their paper which presented the artificial neural networks (ANNs) as a tool for Transient Stability Assessment of a four machine system. In their Artificial Neural Networks the system operation variables such as generators output power and acceleration are used as inputs while the output is the critical fault clearing time (CCT). They have also presented different Types of Artificial Neural Networks which are fed with values of the energy function as inputs. These values of the energy function are evaluated at fractions of seconds after the fault inception. The results show that the value of the energy function has strong correlation with the critical fault clearing time (CCT). [40]

D. R. Marpaka, M. Bodruzzaman, S. S. Devgan, S. M. Aghili and S. Kari developed Artificial Neural Networks (ANNs) which determine the Critical Fault Clearing Times of a two machine power system [41]. Their work was implemented in two phases (training and testing). In the training phase, the Artificial Neural Networks (ANNs) were presented with the angular positions and angular velocities of the last switching operation representing stable, and possibly unstable, conditions. A backpropagation algorithm was used to update the neurons weights and thresholds. In the testing phase, the Artificial Neural Networks (ANNs) were presented with sets of data representing different operating conditions. Their work presented a comparison of the performance of different Artificial Neural Networks with different number of layers which have different number of Neurons in these layers. The comparison was made to determine the optimum number of hidden layer and the optimum number of neurons in these layers for minimum least mean square errors and rapid convergence.

In view of the above, it can be stated that the artificial neural networks (ANNs) are feasible techniques for the transient stability assessment (TSA). The following chapter explores the extended equal area criterion method. The method will be used for developing and training ANNs to provide estimates, within acceptable accuracy, for the critical fault clearing time of a power system.

CHAPTER V

Extended Equal Area Criterion Method

5.1 INTRODUCTION

In this chapter, the derivation of the critical fault clearing time based on the Extended Equal Area Criterion (EEAC) method is presented. The EEAC is a simple direct transient stability assessment method. It attempts to combine and amplify the advantages of the Lyapunov approaches while circumventing some of their major deficiencies.

In the transient stability analysis using the EEAC method, the multi-machine system is decomposed, for an assigned contingency, into two subsets: the critical cluster and the remaining group of machines. The two subsets are transformed into two equivalent machines which are reduced into "One-Machine-Infinite-Bus" (OMIB) system. The critical clearing time is obtained by relating the OMIB angle to its corresponding time with a suitably truncated Taylor series. Computing the CCT, using the EEAC method, is derived in sections (5.2-5.5). The technique of determining the critical fault clearing time (CCT) using the EEAC method is illustrated by conducting a study of a nine-bus system.

5.2 MULTI-MACHINE SYSTEM

The response of an n-machine system following a disturbance is descried by:

$$\frac{d\delta_i}{dt} = \omega_i \tag{5.1}$$

$$M_i \frac{d\omega_i}{dt} = P_{mi} - P_{ei} \qquad i = 1,2,\ldots..n \tag{5.2}$$

$$P_{ei} = E_i^2 Y_{ii} \cos\theta_{ii} + \sum_{j=1, j\neq i}^{n} E_i \, E_j Y_{ij} \cos(\delta_i - \delta_j - \theta_{ij}) \tag{5.3}$$

where

δ_i	rotor angle
ω_i	rotor speed
M_i	inertia coefficient
P_{mi}	mechanical power
P_{ei}	electrical power
E_i	Generator's internal voltage
Y	reduced admittance matrix
Y_{ij}	the ij-th element of the reduced admittance matrix

M_i , P_{mi} and E_i are assumed to be constant.
All loads are modelled as constant impedances.

5.3 *EQUIVALENT TWO MACHINES*

The system's machines are to be divided into two groups: a critical cluster and the remaining stable machines sets. The following notation will be used in the rest of this chapter:

s denotes a critical machine,

S denotes the critical cluster,

a denotes a stable machine, and

A denotes the group of all remaining machines.

The following derivations will be based on the following assumption:
$\delta_l = \delta_a \quad \forall\, l \in A$ and $\delta_k = \delta_s \quad \forall\, k \in S$.

Equation (5.3) can be rewritten for the l-th stable machine and the k-th critical machine as follows:

$$P_{el} = E_l^2 Y_{ll} \cos\theta_{ll} + \sum_{j \in S} E_l E_j Y_{lj} \cos(\delta_a - \delta_s - \theta_{lj}) + \sum_{j \in A, j \neq l} E_l E_j Y_{lj} \cos\theta_{lj} \tag{5.4}$$

$$P_{ek} = E_k^2 Y_{kk} \cos\theta_{kk} + \sum_{j \in A} E_k E_j Y_{kj} \cos(\delta_s - \delta_a - \theta_{kj}) + \sum_{j \in S, j \neq k} E_k E_j Y_{kj} \cos\theta_{kj} \tag{5.5}$$

5.4 THE ONE-MACHINE-INFINITE-BUS EQUIVALENT

Let's define δ as:

$$\delta = \delta_s - \delta_a \tag{5.6}$$

Thus, equation (5.4) and equation (5.5) can be expressed as:

$$P_{el} = E_l^2 Y_{ll} \cos\theta_{ll} + \sum_{j \in S} E_l E_j Y_{lj} \cos(\delta + \theta_{lj}) + \sum_{j \in A, j \neq l} E_l E_j Y_{lj} \cos\theta_{lj} \tag{5.7}$$

$$P_{ek} = E_k^2 Y_{kk} \cos\theta_{kk} + \sum_{j \in A} E_k E_j Y_{kj} \cos(\delta - \theta_{kj}) + \sum_{j \in S, j \neq k} E_k E_j Y_{kj} \cos\theta_{kj} \tag{5.8}$$

Equation (5.2) can be rewritten as:

$$M_i \frac{d^2 \delta_i}{dt^2} = P_{mi} - P_{ei} \tag{5.9}$$

Applying equation (5.9) to all machines yields the following relationship:

$$\sum M_i \frac{d^2 \delta_i}{dt^2} = \sum P_{mi} - \sum P_{ei} \tag{5.10}$$

Since it was assumed that

$$\delta_l = \delta_a \qquad \forall l \in a$$

Thus,

$$M_l \frac{d^2 \delta_l}{dt^2} = M_l \frac{d^2 \delta_a}{dt^2} \tag{5.11}$$

Adding all equations obtained by applying equation (5.10) for all stable machines yields the following equation:

$$\Sigma_{l \in A} M_l \frac{d^2 \delta_l}{dt^2} = (\Sigma_{l \in A} M_l) \frac{d^2 \delta_a}{dt^2} \tag{5.12}$$

Let's define M_a as:

$$M_a = \Sigma_{l \in A} M_l \tag{5.13}$$

The following equation is obtained from equation (5.12) and equation (5.13).

$$M_a \frac{d^2 \delta_a}{dt^2} = \Sigma_{l \in A} P_{ml} - P_{el} \tag{5.14}$$

Let's define M_S as:

$$M_s = \Sigma_{k \in S} M_k \tag{5.15}$$

Equation (5.16) is obtained form equation (5.14) and equation (5.15).

$$\frac{d^2 \delta_S}{dt^2} = \frac{\sum_{k \in S} P_{mk} - P_{ek}}{M_S} \tag{5.16}$$

Equation (5.14) can be expressed as:

$$\frac{d^2 \delta_a}{dt^2} = \frac{(\sum_{l \in A} P_{ml} - P_{el})}{M_a} \tag{5.17}$$

Also, equation (5.16) can be rewritten as:

$$\frac{d^2 \delta_S}{dt^2} = \frac{\sum_{k \in S} (P_{mk} - P_{ek})}{M_S} \tag{5.18}$$

From equation (5.16), equation (5.17) and equation (5.18), the following equation is obtained.

$$\frac{d^2\delta}{dt^2} = \frac{d^2\delta_S}{dt^2} - \frac{d^2\delta_a}{dt^2} \tag{5.19}$$

Substituting equation (5.17) and equation (5.18) into equation (5.19) yields that

$$\frac{d^2\delta}{dt^2} = \frac{\sum_{k \in S} (P_{mk} - P_{ek})}{M_s} - \frac{\sum_{l \in A} (P_{ml} - P_{el})}{M_a} \tag{5.20}$$

Let's define M_t and M as follows:

$$M_t = M_s + M_a \tag{5.21}$$

$$M = \frac{M_s M_a}{M_t} \tag{5.22}$$

By substituting equation (5.21) and equation (5.22) into equation (5.20), the following relation is obtained:

$$M\frac{d^2\delta}{dt^2}=\frac{M_a}{M_t}(\Sigma_{k\in S}\ P_{mk}-P_{ek})-\frac{M_s}{M_t}(\Sigma_{l\in A}\ P_{ml}-P_{el}) \tag{5.23}$$

Equation (5.23) can be expressed as:

$$\begin{aligned}\frac{Md^2\delta}{dt^2}&=\frac{M_a\Sigma_{k\in S}\ P_{mk}-M_s\Sigma_{l\in A}\ P_{ml}}{M_t}\\&+\frac{M_s\Sigma_{l\in A}\ P_{el}-M_a\Sigma_{k\in S}\ P_{ek}}{M_t}\end{aligned} \tag{5.24}$$

Let' define P_m and P_e as:

$$P_m=\frac{M_a\Sigma_{k\in S}\ P_{mk}-M_s\Sigma_{l\in A}\ P_{ml}}{M_t} \tag{5.25}$$

$$P_e=\frac{M_s\Sigma_{l\in A}\ P_{el}-M_a\Sigma_{k\in S}\ P_{ek}}{M_t} \tag{5.26}$$

substituting equation (5.25) and equation (5.26), equation (5.24) can be rewritten as:

$$Md^2 \frac{\delta_S}{dt^2} = P_m - P_e \tag{5.27}$$

Equations (5.28) and (5.29) can be obtained form equation (5.7) and equation (5.8).

$$\sum_{l \in A} P_{el} = \sum_{l \in A} E_l^2 Y_{ll} \cos\theta_{ll} + \sum_{j \in S, l \in A} E_l E_j Y_{lj} \cos(\delta + \theta_{lj}) + \sum_{j \in A, l \in A, j \neq l} E_l E_j Y_{lj} \cos\theta_{lj} \tag{5.28}$$

$$\sum_{k \in S} P_{ek} = \sum_{k \in S} E_k^2 Y_{kk} \cos\theta_{kk} + \sum_{j \in A, k \in S} E_k E_j Y_{kj} \cos(\delta - \theta_{lj}) + \sum_{j \in S, k \in S, j \neq k} E_k E_j Y_{kj} \cos\theta_{kj} \tag{5.29}$$

Substituting equation (5.28) and equation (5.29) into equation (5.27) yields that

$$\begin{aligned} M_t P_e = {} & M_s(\sum_{l \in A} E_l^2 Y_{ll} \cos\theta_{ll} + \sum_{j \in A, l \in A, j \neq l} E_l E_j Y_{lj} \cos\theta_{lj}) + M_s(\sum_{j \in S, l \in A} E_l E_j Y_{lj} \cos(\delta + \theta_{lj})) \\ & - M_a(\sum_{k \in S} E_k^2 Y_{kk} \cos\theta_{kk} + \sum_{j \in S, k \in S, j \neq k} E_k E_j Y_{kj} \cos\theta_{kj}) - M_a(\sum_{j \in A, k \in S} E_k E_j Y_{kj} \cos(\delta - \theta_{lj})) \end{aligned} \tag{5.30}$$

Let's define P_c as:

$$P_c = \frac{1}{M_t}[\, M_s(\sum_{l\in A} E_l^2 Y_{ll} \cos\theta_{ll} + \sum_{j\in A, l\in A, j\neq l} E_l E_j Y_{lj} \cos\theta_{lj})$$
$$- M_a(\sum_{k\in S} E_k^2 Y_{kk} \cos\theta_{kk} + \sum_{j\in S, k\in S, j\neq k} E_k E_j Y_{kj} \cos\theta_{kj})] \tag{5.31}$$

Thus, equation (5.30) can be expressed as:

$$P_e = P_c + \frac{1}{M_t}[\, M_s(\sum_{j\in S, l\in A} E_l E_j Y_{lj} \cos(\delta + \theta_{lj})) - M_a(\sum_{j\in A, k\in S} E_k E_j Y_{kj} \cos(\delta - \theta_{lj}))] \tag{5.32}$$

Let's define P(δ) as:

$$P(\delta) = \frac{1}{M_t}[\, M_s(\sum_{j\in S, l\in A} E_l E_j Y_{lj} \cos(\delta + \theta_{lj})) - M_a(\sum_{j\in A, k\in S} E_k E_j Y_{kj} \cos(\delta - \theta_{lj}))] \tag{5.33}$$

So, equation (5.32) can be written as:

$$P_e = P_c + P(\delta) \tag{5.34}$$

The following equation is obtained by manipulating equation (5.33).

$$P(\delta)=\frac{1}{M_t}\sum_{j\in S,l\in A} E_l E_j Y_{lj}[M_s\cos(\delta+\theta_{lj})-M_a\cos(\delta-\theta_{lj})] \tag{5.35}$$

P(δ) can be expressed as:

$$P(\delta)=\frac{1}{M_t}\sum_{j\in S,l\in A} E_l E_j Y_{lj}[M_s\cos\delta\cos\theta_{lj}-M_s\sin\delta\sin\theta_{lj} - M_a\cos\delta\cos\theta_{lj}-M_a\sin\delta\sin\theta_{lj}] \tag{5.36}$$

Equation (5.36) can be expressed as:

$$P(\delta)=\frac{1}{M_t}[\sum_{j\in S,l\in A} E_l E_j Y_{lj}[\cos\delta(M_s\cos\theta_{lj}-M_a\cos\theta_{lj})-\sin\delta(M_s\sin\theta_{lj}+M_a\sin\theta_{lj})] \tag{5.37}$$

Equation (5.37) can be simplified as:

$$P(\delta) = \frac{1}{M_l} \sum_{l \in S, l \in A} E_l E_j Y_{lj} A_{lj} \cos(\delta - B_{lj}) \tag{5.38}$$

Where

$$A_{lj} = \sqrt{(M_s \cos\theta_{lj} - M_a \cos\theta_{lj})^2 + (M_s \sin\theta_{lj} + M_a \sin\theta_{lj})^2} \tag{5.39}$$

and

$$B_{lj} = \tan^{-1}[(M_s \sin\theta_{lj} + M_a \sin\theta_{lj}) / (M_a \cos\theta_{lj} - M_s \cos\theta_{lj})] \tag{5.40}$$

These terms can be simplified into the following:

$$A_{lj} = \sqrt{(\cos\theta_{lj} (M_a - M_s)^2 + (M_s \sin\theta_{lj} (M_s + M_a)^2} \tag{5.41}$$

$$B_{lj} = \tan^{-1} \frac{M_s \sin\theta_{lj} (M_s + M_a)}{\cos\theta_{lj} (M_a - M_s)} \tag{5.42}$$

Let's define K_{lj} as:

$$k_{lj} = E_l E_j Y_{lj} A_{lj} \tag{5.43}$$

Thus, equation (5.38) can be rewritten as:

$$P(\delta) = \frac{1}{M_t} \sum_{j \in S, l \in A} k_{lj} \cos(\delta - B_{lj}) \tag{5.44}$$

Using the exponential definition of the cosine yields the following equations.

$$P(\delta) = \frac{1}{2M_t} \sum_{j \in S, l \in A} k_{lj} [e^{j(\delta - B_{lj})} - e^{-j(\delta - B_{lj})}] \tag{5.45}$$

$$P(\delta) = \frac{1}{2M_t} \sum_{j \in S, l \in A} k_{lj} (e^{-jB_{lj}} e^{j\delta} - e^{jB_{lj}} e^{-j\delta}) \tag{5.46}$$

$$P(\delta) = \frac{1}{2M_t}\left(\sum_{j \in S, l \in A} k_{lj} e^{-jB_{lj}} e^{j\delta} - \sum_{j \in S, l \in A} k_{lj} e^{jB_{lj}} e^{-j\delta} \right) \tag{5.47}$$

$$P(\delta) = \frac{1}{2M_t}\left[\left(\sum_{j \in S, l \in A} k_{lj} e^{-jB_{lj}} \right) e^{j\delta} - \left(\sum_{j \in S, l \in A} k_{lj} e^{jB_{lj}} \right) e^{-j\delta} \right] \tag{5.48}$$

$$P(\delta) = \frac{1}{2M_t} \sum_{j \in S, l \in A} k_{lj} e^{-jB_{lj}} (\cos\delta + j\sin\delta) - \frac{1}{2M_t} \sum_{j \in S, l \in A} k_{lj} e^{jB_{lj}} (\cos\delta - j\sin\delta) \tag{5.49}$$

$$P(\delta) = \frac{1}{2M_t} \sum_{j \in S, l \in A} \left[(\cos\delta) k_{lj} \left(e^{-jB_{lj}} - e^{jB_{lj}}\right) + (\sin\delta) j k_{lj} \left(e^{-jB_{lj}} + e^{jB_{lj}}\right) \right] \tag{5.50}$$

$$P(\delta) = \frac{1}{M_t} \sum_{j \in S, l \in A} \left[\frac{(\cos\delta) k_{lj} (-2j)(e^{jB_{lj}} - e^{-jB_{lj}})}{2j} + \frac{(\sin\delta)(2) j k_{lj} (e^{-jB_{lj}} + e^{jB_{lj}})}{2} \right]$$

(5.51)

$$P(\delta)=\frac{1}{M_t}\sum_{j\in S, l\in A}\left[\frac{(\cos\delta)k_{lj}(-j)(e^{jB_{lj}}-e^{-jB_{lj}})}{2j}+\frac{(\sin\delta)jk_{lj}(e^{-jB_{lj}}+e^{jB_{lj}})}{2}\right] \tag{5.52}$$

$$P(\delta)=\frac{1}{M_t}\sum_{j\in S, l\in A}(jk_{lj}\sin\delta\cos B_{lj}-jk_{lj}\cos\delta\sin B_{lj}) \tag{5.53}$$

$$P(\delta)=\frac{1}{M_t}\sum_{j\in S, l\in A}jk_{lj}(\sin\delta\cos B_{lj}-\cos\delta\sin B_{lj}) \tag{5.54}$$

Let's define N_{lj} as:

$$N_{lj}=jk_{lj} \tag{5.55}$$

So, equation (5.54) can be expressed as:

$$P(\delta)=\frac{1}{M_t}\sum_{j\in S,l\in A} N_{lj}(\sin\delta\cos B_{lj}-\cos\delta\sin B_{lj}) \tag{5.56}$$

The following equations are obtained by manipulating the previous equation.

$$P(\delta)=\frac{1}{M_t}\sum_{j\in S,l\in A} N_{lj}\sin(\delta-B_{lj}) \tag{5.57}$$

$$P(\delta)=\frac{1}{M_t}\sum_{j\in S,l\in A} N_{lj}\cos(\delta-B_{lj}-\tfrac{\pi}{2}) \tag{5.58}$$

P(δ) can be expressed as:

$$P(\delta)=\frac{1}{M_t}\sum_{j\in S,l\in A} (N_{1lj}\cos\delta+N_{2lj}\sin\delta) \tag{5.59}$$

Where N_{1lj} and N_{2lj} can be obtained by solving the following two equations.

$$N_{lj} = \sqrt{N_{1lj}^{\ 2} + N_{1lj}^{\ 2}} \tag{5.60}$$

and

$$\tan(B_{lj} + \frac{\pi}{2}) = \frac{N_{2lj}}{N_{1lj}} \tag{5.61}$$

Equation (5.59) can be expressed as:

$$P(\delta) = \frac{1}{M_t}[\cos\delta \sum_{j\in S, l\in A} N_{1lj} + \sin\delta \sum_{j\in S, l\in A} N_{2lj}] \tag{5.62}$$

Consequently, the following equation is obtained.

$$P(\delta) = \frac{N}{M_l}\cos(\delta - B) \tag{5.63}$$

where

$$N = \sqrt{\left(\sum_{j \in S, l \in A} N_{1lj}\right)^2 + \left(\sum_{j \in S, l \in A} N_{2lj}\right)^2} \tag{5.64}$$

and

$$B = \tan^{-1} \frac{\sum_{j \in S, l \in A} N_{2lj}}{\sum_{j \in S, l \in A} N_{1lj}} \tag{5.65}$$

The following equation is obtained form equation (5.63).

$$P(\delta) = \frac{N}{M_t} \sin(\delta - B + \frac{\pi}{2}) \tag{5.66}$$

Let's define ν and P_{max} as:

$$\nu = B - \frac{\pi}{2} \tag{5.67}$$

$$P_{\max} = \frac{N}{M_t} \tag{5.68}$$

By substituting equation (5.67) and equation (5.68) into equation (5.66), the following equation is obtained.

$$M\frac{d^2\delta}{dt^2} = P_m - [P_c + P_{max}\sin(\delta - v)] \tag{5.69}$$

This equation is called the One-Machine-Infinite-Bus (OMIB) equation.

5.5 EQUAL AREA CRITERION APPLIED TO ONE-MACHINE-INFINITE BUS SYSTEM

Applying the equal area criterion principle to the previous equation (5.69), a stability margin can be defined as:

$$\eta = A_{dec} - A_{acc} \tag{5.70}$$

The sign of this stability margin indicates whether the system is stable or not.

The A_{acc} and A_{dec} are define in the following:

$$A_{acc} = (P_m - P_{cD})(\delta_\tau - \delta_o) + P_{\max D}[\cos(\delta_\tau - \nu_D) - \cos(\delta_o - \nu_D)] \tag{5.71}$$

$$A_{dec} = (P_{cP} - P_m)(\pi - \delta_\tau - \delta_P + 2\nu_P) + P_{\max P}[\cos(\delta_\tau - \nu_P) - \cos(\delta_P - \nu_P)] \tag{5.72}$$

Where

O : *original (pre-fault)*

D : *during-fault*

P : *post-fault.*

$\delta\tau$: *represents the critical clearing angle.*

At the critical clearing time, the transient stability margin should be zero:

$$\eta = A_{dec} - A_{acc} = 0 \tag{5.73}$$

So, the critical clearing angle can be obtained by solving the previous equation.

The CCT can be computed using the Taylor series expansion of the critical clearing angle:

$$\delta_\tau = \delta_o + \frac{1}{2}\gamma\tau^2 + \frac{1}{24}\gamma^{(2)}\tau^4 + \frac{1}{720}\gamma^{(4)}\tau^6 + \ldots\ldots \tag{5.74}$$

Where γ denotes the acceleration and τ denotes the critical fault clearing time.

The critical fault clearing time can be obtained solving equation (5.74) truncated after the τ^4 term.

5.6 NUMERICAL EXAMPLE

The Extended Equal Area Criterion technique of solving a classical transient stability problem is illustrated by conducting a study of the nine-bus-three-machines system [42], the data for which is given in Figures 5.1 and Tables 5.1, 5.2 and 5.3. The disturbance initiating the transient is a three-phase fault occurring near bus 7 at the end of line 5-7. The following computations are performed using the previous section' notations.

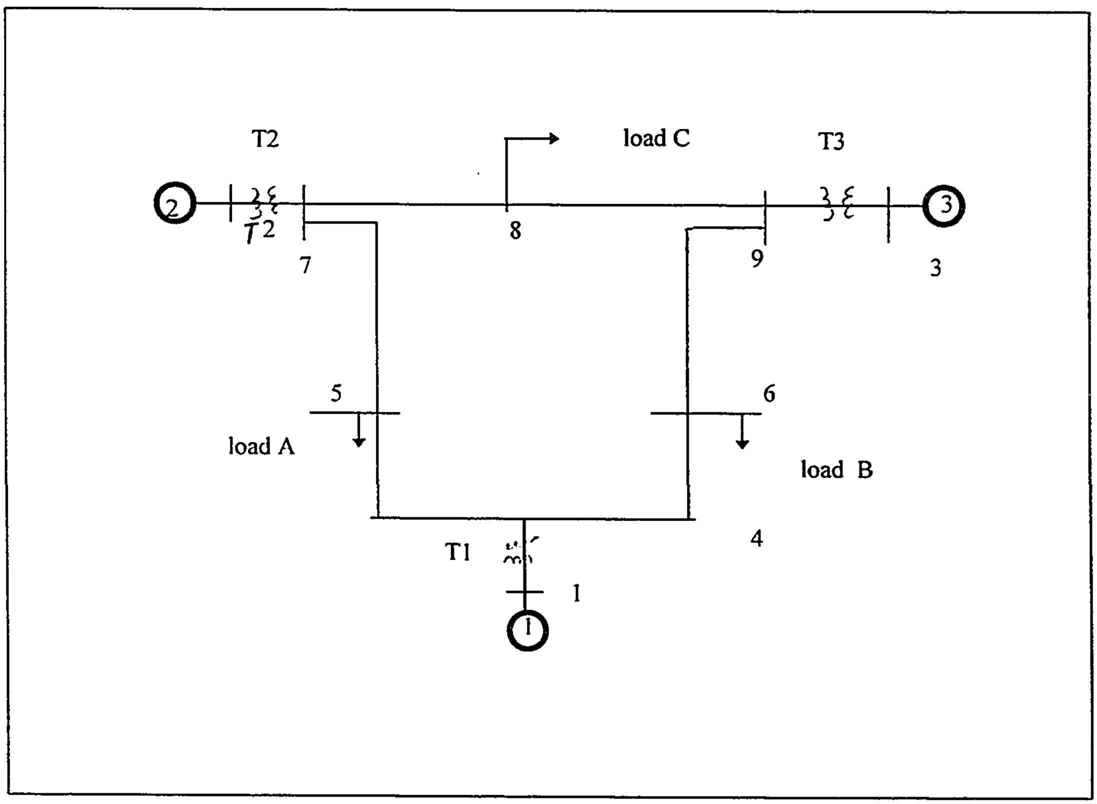

Figure 5.1 Nine-bus system impedance diagram

Transformer	Reactance (p.u.)	Transformation
1	0.0625	18 KV / 230 KV
2	0.0586	13.8 KV / 230 KV
3	0.0576	16.5 KV / 230 KV

Table 5.1 Transformers data

From Bus	To Bus	Resistance (p.u.)	Reactance (p.u.)	Susceptance(p.u.)
7	8	0.0085	0.0720	0.149
8	9	0.0119	0.1008	0.209
9	6	0.0390	0.1700	0.358
6	4	0.0170	0.0920	0.158
4	5	0.0100	0.0850	0.176
5	7	0.0320	0.1610	0.306

Table 5.2 Transmission lines data

Generator	1	2	3
Rated MVA	247.5	192.0	128.0
Rated Voltage (kV)	16.5	18.0	13.8
Type	hydro	steam	steam
Speed	180 rev/min	3600 rev/min	3600 rev/min
X'd (P.U.)	0.0608	0.1198	0.1813
Stored energy at rated speed	2364 MW.S	640 MW.S	301 MW.S

Table5.3 Generators data

For the purpose of this study the generators are represented by the classical model and the loads by constant impedances. The damping torques are neglected. The system base is 100 MVA.

The equivalent shunt admittance for the loads are given in p.u. as load A: $\bar{y}_{L5} = 1.2610 - j0.5044$

load B: $\bar{y}_{L6} = 0.8777 - j0.2926$

load C: $\bar{y}_{L8} = 0.9690 - j0.3391$

The generator internal voltages and their initial angles are given in p.u. by

$$E_1\angle\delta_{10} = 1.0566\angle 2.2710^{o}$$

$$E_2\angle\delta_{20} = 1.0502\angle 19.7315^{o}$$

$$E_3\angle\delta_{30} = 1.0170\angle 13.1752^{o}$$

The generators outputs, given in p.u., are

$P_1 = 0.716$	$Q_1 = 0.270$
$P_2 = 1.63$	$Q_2 = 0.067$
$P_3 = 0.85$	$Q_3 = -0.109$

The following results are a summary of a program output, written in FORTRAN Language, on the basis of the previous sections' derivation of the critical fault clearing time (CCT).

$$Y_{reduced}^{prefault} = \begin{bmatrix} 0.846-j2.988 & 0.287+j1.513 & 0.210+j1.226 \\ 0.287+j1.513 & 0.420-j2.724 & 0.213+j1.088 \\ 0.210+j1.226 & 0.213+j1.088 & 0.277-j2.368 \end{bmatrix}$$

$$Y_{reduced}^{faulted} = \begin{bmatrix} 0.657 - j3.816 & 0.000 + j0.000 & 0.070 + j0.631 \\ 0.000 + j0.000 & 0.000 - j5.486 & 0.000 + j0.000 \\ 0.070 + j0.631 & 0.000 + j0.000 & 0.273 - j2.342 \end{bmatrix}$$

$$Y_{reduced}^{fault\ cleared} = \begin{bmatrix} 1.181 - j2.229 & 0.138 + j0.726 & 0.191 + j1.079 \\ 0.138 + j0.726 & 0.289 - j1.953 & 0.199 + j1.229 \\ 0.191 + j1.079 & 0.199 + j1.229 & 0.273 - j2.342 \end{bmatrix}$$

The initial acceleration of a generator is defined by

$$\gamma_i = \frac{[P_{mi} - P_{ei}(\delta(t_o^+))]}{M_i}$$

The initial accelerations of the generators are found to be

$$\gamma_1 = 0.270$$
$$\gamma_2 = 92.175$$
$$\gamma_3 = 43.079$$

Since γ_2 is much greater than both γ_1 and γ_3, generator two is assumed to be the only critical machine. Thus, the following values are obtained.

$$M_a = 0.063$$
$$M_s = 0.18$$
$$M_T = 0.08$$
$$P_{ms} = 1.63$$
$$P_{ma} = 1.566$$
$$P_m = 0.931$$

	Prefault	During-fault	Post-fault
ν	-0.108	0.000	-0.096
$P_{\max}$	2.774	0.000	2.077
P_c	-0.016	-0.228	-0.112
$\delta(rad)$	0.241		0.430

$$\delta_u(rad) = 2.708$$

$$\delta_{critical}(rad) = 1.139$$

This critical angle corresponds to a $0.24*10^{-6}$ stability margin (A_{acc}-A_{dec}). The critical fault clearing time (CCT) is found to be 0.146 seconds (8.78 cycles on a 60 Hz. frequency).

CHAPTER VI

Results on Using Artificial Neural Networks for Estimating the Critical Fault Clearing Time

Artificial Neural Networks have been adapted for estimating the CCT for a power system. Section 6.2 includes a description of the ANNs used for obtaining estimates of the CCT. Section 6.3 Summarize the procedure of training sample generation. Section 6.4 presents a summary of the results.

6.1 Test system

The working example used in this study is the simple three-machines-nine-buses system [42] described in section 5.6.

6.2 Structure of Artificial Neural Networks

The Artificial Neural Networks, trained to generate critical fault clearing time, have a common structure. The ANNs consist of two layers: a hidden layer consisting of thirty neurons and an output layer consisting of a single output neuron. The input signals consists of real generators power (P_{g1}, P_{g2} and P_{g3}), reactive generators power (Q_{g1}, Q_{g2}, and Q_{g3}), loads demands represented with their equivalent impedances (R_a, R_b, R_c, L_a, L_b, and L_c).

The ANNs have been trained for two cases. In the first case, Artificial Neural Networks were trained to provide the fault critical clearing times for the three-machines-nine-buses systems with all of its transmission lines in service. In the seconded case the Artificial Neural Networks were trained to provide the fault critical clearing times for this system provided that a transmission line may not be in services at the instants of the faults occurrence. Figure 6.2 and 6.3 shows the ANNs used for the two cases. For the second case, an additional input was provided to the Artificial Neural Networks. This input is a coded signal representing the transmission line which is not in service at the instant of the fault' occurrence.

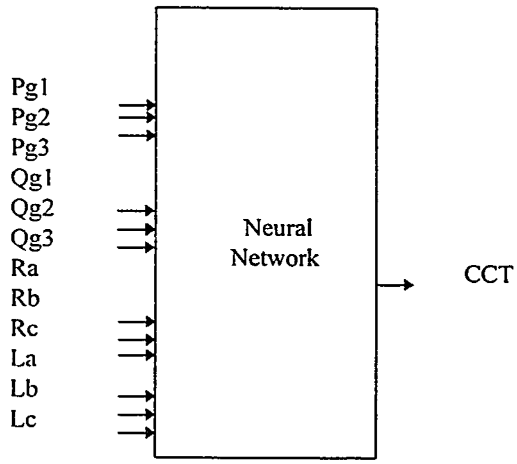

Figure 6.1 ANN used for Case-one

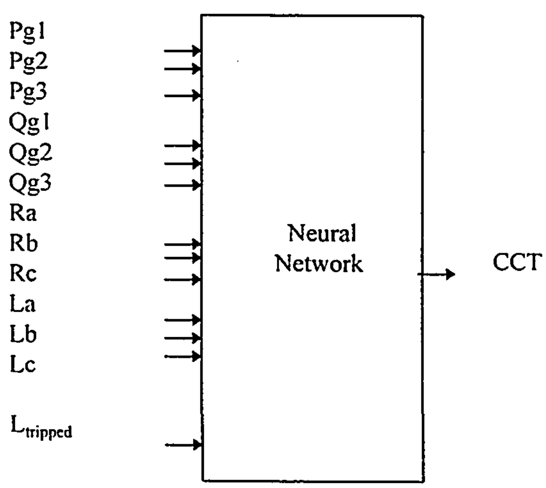

Figure 6.2 ANN used for Case-two

6.3 Generation of Training Samples

Training samples were generated, randomly, for loads at sites A, B, and C. For each load sample, the generators nodes were assigned a random voltage levels. Loading conditions of the generators were computed based on the values of the loads and voltages. Upper and lower limits imposed on the system's parameters are summarized in Table 6.4. The critical fault clearing time is computed for different loading conditions at different faulty nodes using the Extended Equal Area Criterion method.

Different neural networks have been trained to compute the critical fault clearing time for faults at different nodes. The results are shown in the next section. The generators'' internal voltage angles are limited to be within (-10.0) and (+10.0) degrees.

Node No.	P(p.u.)		Q(p.u)		V(p.u.)	
	Lower	Upper	Lower	Upper	Lower	Upper
1	0.65	1.5	0.0	0.5	0.9	1.1
2	0.65	1.5	0.0	0.5	0.9	1.1
3	0.65	1.5	0.0	0.5	0.9	1.1
4	0.0	0.0	0.0	0.0	-	-
5	-1.5	-0.5	-2.0	0.0	-	-
6	-1.5	-0.5	-2.0	0.0	-	-
7	0.0	0.0	0.0	0.0	-	-
8	-1.5	-0.5	-2.0	0.0	-	-
9	0.0	0.0	0.0	0.0	-	-

Table 6.1 Upper and Lower Limits

6.4 *Results*

The following tables and figures summarize the results of training the Artificial Neural Networks described previously in this Chapter. The figures shows the outputs of these ANNs verses the actual Critical Fault Clearing Times computed with the Extended Equal Area Criterion method. The tables illustrate randomly selected testing samples of the inputs and outputs of the trained ANNs and the actual CCTs.

Figures 6.1-6.6 show the comparison of the assessment of CCT by the ANNs with that by the Extended Equal Area Criterion method. Figures 6.3-6.5 show the output of the ANN for the first case for faults at Buses 7, 8 and 9 respectively. Figures 6.6-6.8 show the output of the ANN for the second case for faults at Buses 7, 8 and 9 respectively.

Tables 6.2 show randomly selected samples of the inputs and outputs of the ANN trained for the first case for faults at Bus-7 and the actual CCT values obtained by the EEAC method. Tables 6.3-6.7 presents samples of inputs and outputs of the ANNs and the CCT values for the first case and second case for faults at Buses 7, 8 and 9.

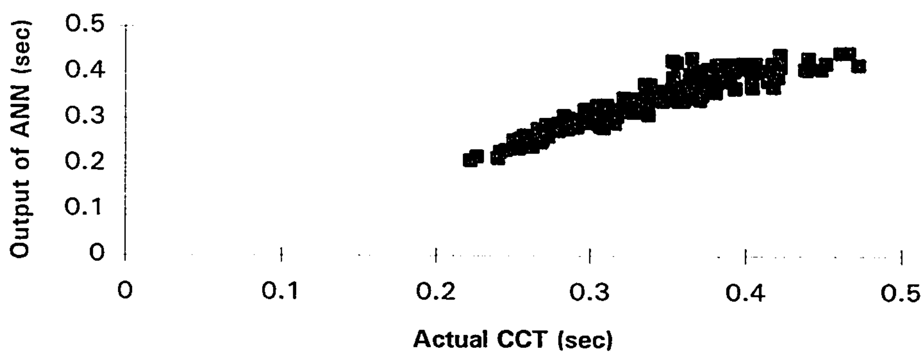

Figure 6.3 Output of The ANN for the first case for Faults at Bus-7

P_g (1)	P_g (2)	P_g(3)	Q_g (1)	Q_g (2)	Q_g (3)	R_a	R_b	R_c	L_a	L_b	L_c	Actual CCT	ANN output
1.43	0.76	0.78	0.25	0.37	0.41	0.92	0.70	1.07	0.46	0.16	0.41	0.44	0.41
0.89	0.83	0.78	0.14	0.01	0.39	1.04	1.03	1.10	0.11	0.42	0.44	0.35	0.34
1.38	0.84	0.89	0.31	0.05	0.43	0.96	0.67	1.08	0.24	0.21	0.12	0.38	0.37
1.32	0.79	1.01	0.17	0.16	0.42	0.78	0.94	0.90	0.06	0.64	0.11	0.35	0.39
1.42	1.13	0.75	0.41	0.18	0.45	0.78	0.66	1.00	0.23	0.16	0.21	0.27	0.28
1.32	0.92	0.84	0.20	0.12	0.34	0.71	0.76	1.82	0.14	0.19	0.22	0.36	0.34
1.20	0.78	0.85	0.02	0.06	0.30	1.05	0.81	1.53	0.17	0.16	0.30	0.38	0.38
1.43	1.22	0.92	0.13	0.01	0.34	0.96	0.67	0.97	0.05	0.05	0.07	0.26	0.26
1.48	1.17	0.97	0.25	0.28	0.47	0.78	0.75	0.76	0.01	0.27	0.18	0.31	0.28
1.02	0.86	0.85	0.19	0.20	0.43	0.74	1.08	1.03	0.10	0.73	0.39	0.34	0.35
1.39	0.97	0.72	0.30	0.32	0.44	1.03	0.69	0.84	0.57	0.13	0.29	0.32	0.33
1.15	1.18	0.70	0.23	0.21	0.40	1.42	0.68	0.82	0.57	0.23	0.10	0.25	0.25
1.37	1.23	0.75	0.05	0.20	0.30	1.34	0.66	0.94	0.10	0.17	0.04	0.26	0.25
1.24	1.10	0.77	0.08	0.10	0.28	1.10	0.75	0.94	0.74	0.01	0.02	0.28	0.28
1.23	1.04	0.78	0.28	0.41	0.45	0.79	0.66	1.16	0.23	0.19	0.67	0.29	0.29
1.28	0.80	0.87	0.30	0.06	0.49	1.15	0.76	0.80	0.10	0.26	0.28	0.38	0.38
1.27	0.91	0.76	0.37	0.06	0.47	0.70	1.15	0.78	0.24	0.03	0.31	0.33	0.34
0.91	0.98	0.84	0.25	0.16	0.45	1.12	1.00	0.70	0.62	0.55	0.09	0.32	0.29
1.35	0.98	0.73	0.20	0.40	0.38	0.68	1.31	0.85	0.23	0.46	0.23	0.33	0.34
1.34	0.70	0.98	0.25	0.04	0.45	1.11	0.66	1.06	0.07	0.25	0.22	0.38	0.42

Table 6.2 Examples of Training data and Output of The ANN for the first case (Faults at Bus-7)

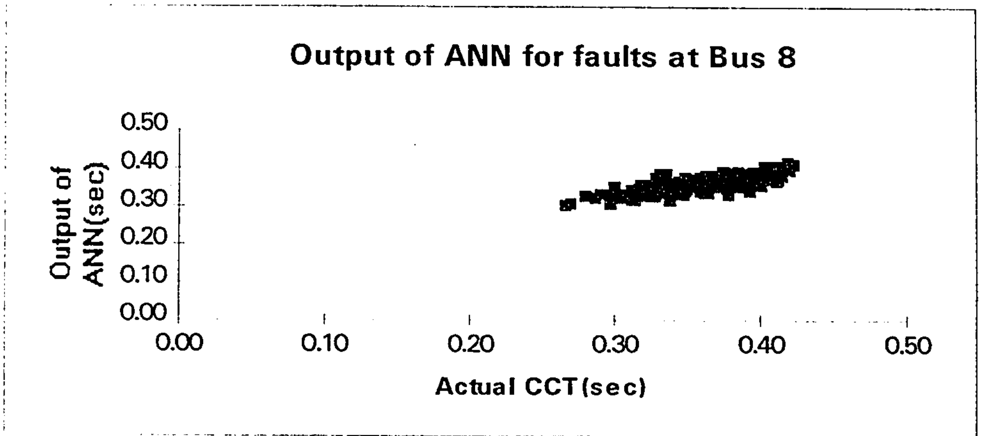

Figure 6.4 Output of The ANN for the first case for Faults at Bus-8

P_g (1)	P_g (2)	P_g(3)	Q_g (1)	Q_g (2)	Q_g (3)	R_a	R_b	R_c	L_a	L_b	L_c	Actual CCT	ANN output
1.18	1.24	0.74	0.17	0.44	0.45	1.19	0.84	0.65	0.25	0.28	0.23	0.36	0.37
1.28	1.01	0.85	0.23	0.28	0.45	0.99	0.72	0.88	0.15	0.24	0.32	0.40	0.37
0.81	0.95	0.88	0.12	0.03	0.39	1.19	1.46	0.69	0.75	0.39	0.06	0.35	0.36
1.41	1.12	0.93	0.28	0.16	0.49	0.99	0.78	0.66	0.15	0.13	0.17	0.36	0.35
1.02	0.95	0.89	0.19	0.26	0.39	0.91	0.83	0.95	0.54	0.37	0.03	0.38	0.35
1.27	0.89	1.03	0.24	0.30	0.42	0.69	0.82	1.10	0.22	0.39	0.04	0.32	0.33
1.15	1.15	0.90	0.05	0.41	0.41	1.46	0.84	0.68	0.52	0.19	0.16	0.35	0.35
1.30	0.67	0.94	0.17	0.24	0.44	0.84	0.80	1.06	0.12	0.18	0.79	0.35	0.38
1.49	1.15	0.73	0.43	0.38	0.48	0.61	0.68	1.02	0.20	0.07	0.62	0.42	0.41
1.00	1.03	0.72	0.22	0.49	0.46	0.97	0.95	0.73	0.57	0.43	0.27	0.40	0.38
1.02	1.02	0.98	0.18	0.38	0.42	1.02	0.66	0.88	0.99	0.21	0.06	0.35	0.34
1.01	0.99	1.00	0.13	0.45	0.49	1.17	0.92	0.63	0.89	0.15	0.21	0.33	0.33
1.01	0.89	0.78	0.13	0.07	0.38	1.03	0.92	1.01	0.45	0.00	0.43	0.42	0.39
1.36	1.10	0.77	0.46	0.04	0.46	0.73	0.65	1.15	0.13	0.21	0.15	0.39	0.39
1.10	0.88	0.91	0.10	0.24	0.41	0.98	1.23	0.76	0.25	0.49	0.19	0.36	0.35
1.12	1.02	0.91	0.11	0.37	0.42	1.18	0.72	0.89	0.45	0.11	0.38	0.37	0.36
1.34	1.02	0.80	0.32	0.19	0.48	0.81	1.01	0.68	0.26	0.12	0.24	0.41	0.37
1.26	1.16	0.76	0.34	0.13	0.44	0.70	0.92	0.84	0.09	0.52	0.12	0.37	0.37
1.50	1.17	0.81	0.02	0.17	0.32	1.13	0.85	0.75	0.03	0.10	0.12	0.40	0.36
1.45	1.35	0.97	0.17	0.44	0.45	0.83	0.71	0.75	0.06	0.14	0.22	0.32	0.34
1.12	1.12	1.04	0.24	0.15	0.45	1.05	0.73	0.72	0.73	0.11	0.03	0.32	0.33

Table 6.3 Examples of Training data and Output of The ANN for the first case (Faults at Bus-8)

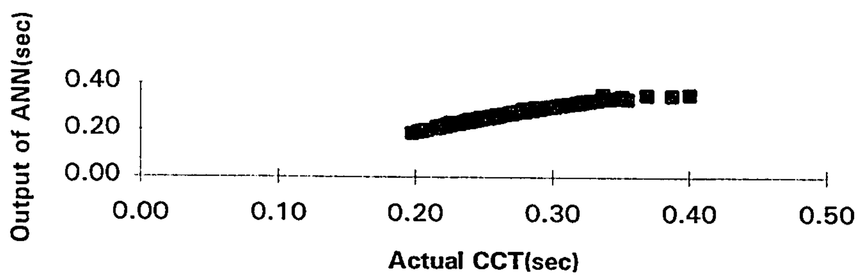

Figure 6.5 Output of The ANN for the first case for Faults at Bus-9

P_g (1)	P_g (2)	P_g(3)	Q_g (1)	Q_g (2)	Q_g (3)	R_a	R_b	R_c	L_a	L_b	L_c	Actual CCT	ANN output
1.47	1.02	0.96	0.27	0.05	0.39	0.74	0.73	1.02	0.23	0.01	0.13	0.25	0.25
1.43	0.76	0.78	0.25	0.37	0.41	0.92	0.70	1.07	0.46	0.16	0.41	0.29	0.29
0.89	0.83	0.78	0.14	0.01	0.39	1.04	1.03	1.10	0.11	0.42	0.44	0.26	0.27
1.38	0.84	0.89	0.31	0.05	0.43	0.96	0.67	1.08	0.24	0.21	0.12	0.26	0.26
1.32	0.79	1.01	0.17	0.16	0.42	0.78	0.94	0.90	0.06	0.64	0.11	0.22	0.22
1.42	1.13	0.75	0.41	0.18	0.45	0.78	0.66	1.00	0.23	0.16	0.21	0.32	0.32
1.32	0.92	0.84	0.20	0.12	0.34	0.71	0.76	1.82	0.14	0.19	0.22	0.27	0.27
1.20	0.78	0.85	0.02	0.06	0.30	1.05	0.81	1.53	0.17	0.16	0.30	0.26	0.26
1.43	1.22	0.92	0.13	0.01	0.34	0.96	0.67	0.97	0.05	0.05	0.07	0.26	0.27
1.48	1.17	0.97	0.25	0.28	0.47	0.78	0.75	0.76	0.01	0.27	0.18	0.25	0.25
1.02	0.86	0.85	0.19	0.20	0.43	0.74	1.08	1.03	0.10	0.73	0.39	0.25	0.25
1.39	0.97	0.72	0.30	0.32	0.44	1.03	0.69	0.84	0.57	0.13	0.29	0.33	0.33
1.15	1.18	0.70	0.23	0.21	0.40	1.42	0.68	0.82	0.57	0.23	0.10	0.34	0.33
1.37	1.23	0.75	0.05	0.20	0.30	1.34	0.66	0.94	0.10	0.17	0.04	0.33	0.32
1.15	0.66	0.97	0.24	0.03	0.49	1.14	0.89	0.82	0.14	0.37	0.26	0.22	0.22
1.24	1.10	0.77	0.08	0.10	0.28	1.10	0.75	0.94	0.74	0.01	0.02	0.31	0.31
1.23	1.04	0.78	0.28	0.41	0.45	0.79	0.66	1.16	0.23	0.19	0.67	0.29	0.29
1.28	0.80	0.87	0.30	0.06	0.49	1.15	0.76	0.80	0.10	0.26	0.28	0.26	0.26
1.27	0.91	0.76	0.37	0.06	0.47	0.70	1.15	0.78	0.24	0.03	0.31	0.29	0.30
0.91	0.98	0.84	0.25	0.16	0.45	1.12	1.00	0.70	0.62	0.55	0.09	0.26	0.26
1.35	0.98	0.73	0.20	0.40	0.38	0.68	1.31	0.85	0.23	0.46	0.23	0.31	0.31

Table 6.4 Examples of Training data and Output of The ANN for the first case (Faults at Bus-9)

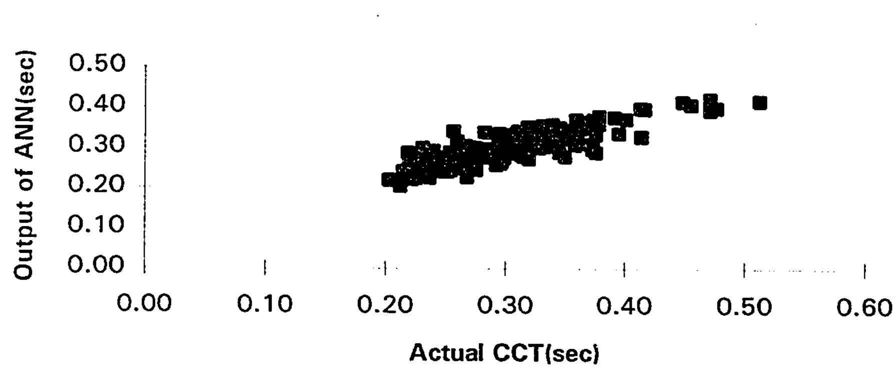

Figure 6.6 Output of The ANN for the second case for Faults at Bus-7

P_g (1)	P_g (2)	P_g(3)	Q_g (1)	Q_g (2)	Q_g (3)	R_a	R_b	R_c	L_a	L_b	L_c	L_{trip}	Actual CCT	ANN output
0.89	0.82	0.68	0.12	0.15	0.43	0.87	0.76	1.69	0.45	0.21	0.23	4	0.32	0.31
1.13	1.10	1.32	0.09	0.24	0.47	0.71	1.05	0.82	0.15	0.12	0.03	5	0.24	0.28
0.89	1.09	1.31	0.05	0.24	0.45	0.87	0.90	0.92	0.34	0.02	0.02	5	0.23	0.27
1.20	0.93	0.79	0.47	0.20	0.35	0.72	1.29	0.72	0.28	0.31	0.24	7	0.28	0.26
1.16	0.96	0.68	0.32	0.10	0.44	0.93	1.57	0.63	0.22	0.64	0.19	6	0.27	0.29
1.50	0.97	0.79	0.19	0.02	0.15	0.75	0.69	1.76	0.10	0.02	0.08	9	0.28	0.30
1.37	0.76	1.03	0.15	0.14	0.40	0.87	0.80	1.18	0.25	0.16	0.03	8	0.31	0.34
1.25	0.83	0.85	0.31	0.24	0.45	0.76	1.21	0.69	0.34	0.94	0.08	0	0.38	0.38
1.46	1.26	0.73	0.21	0.10	0.23	0.92	1.04	0.76	0.22	0.12	0.04	6	0.22	0.25
1.03	1.26	0.67	0.10	0.34	0.40	0.81	0.75	1.34	0.01	0.25	0.52	4	0.23	0.25
0.93	1.05	0.72	0.02	0.27	0.36	0.73	1.06	1.60	0.17	0.46	0.25	5	0.28	0.29
0.93	0.86	0.77	0.33	0.04	0.46	0.83	1.28	0.80	0.33	0.87	0.14	0	0.35	0.34
1.43	0.77	0.89	0.34	0.19	0.39	1.07	0.64	1.04	0.09	0.20	0.43	6	0.36	0.34
1.05	0.73	0.68	0.16	0.24	0.19	0.98	0.90	1.37	0.21	0.27	0.74	9	0.34	0.32
1.20	0.72	0.80	0.13	0.02	0.13	1.20	1.33	0.87	0.47	0.17	0.08	7	0.33	0.30
1.27	0.89	0.85	0.32	0.10	0.13	1.16	0.85	0.85	0.24	0.36	0.05	7	0.29	0.29
1.11	0.84	0.96	0.35	0.10	0.44	1.29	0.85	0.71	0.58	0.38	0.13	6	0.32	0.31
1.49	0.97	0.94	0.29	0.08	0.38	1.03	0.83	0.74	0.13	0.20	0.12	6	0.32	0.31
1.27	1.12	0.66	0.42	0.32	0.18	0.82	0.79	0.71	0.40	0.05	0.14	9	0.23	0.24
1.25	0.88	0.70	0.39	0.30	0.25	0.72	1.30	0.85	0.25	0.45	0.33	7	0.31	0.28

Table 6.5 Examples of Training data and Output of The ANN for the second case (Faults at Bus-7)

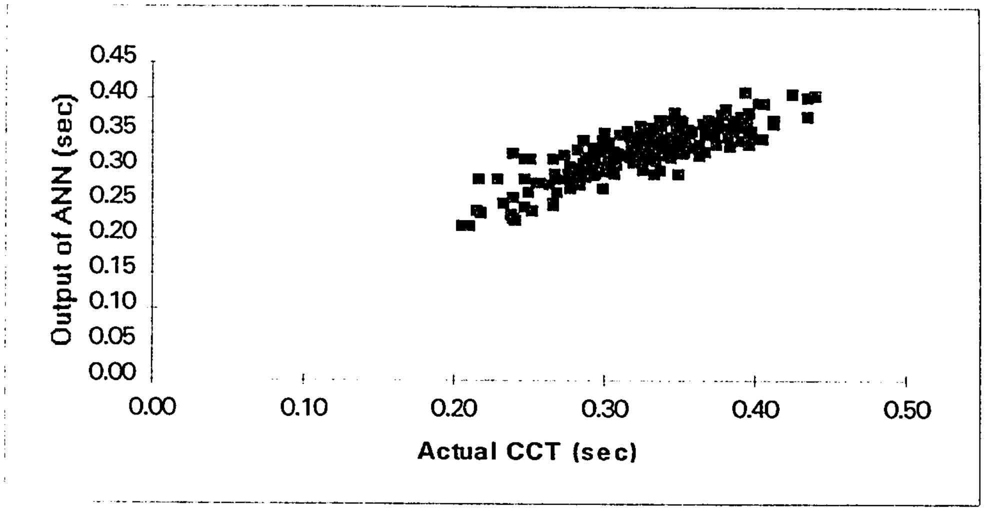

Figure 6.7 Output of The ANN for the second case for Faults at Bus-8

P_g (1)	P_g (2)	P_g(3)	Q_g (1)	Q_g (2)	Q_g (3)	R_a	R_b	R_c	L_a	L_b	L_c	L_{trip}	Actual CCT	ANN output
0.89	0.82	0.68	0.12	0.15	0.43	0.87	0.76	1.69	0.45	0.21	0.23	4	0.39	0.35
1.13	1.10	1.32	0.09	0.24	0.47	0.71	1.05	0.82	0.15	0.12	0.03	5	0.21	0.22
0.89	1.09	1.31	0.05	0.24	0.45	0.87	0.90	0.92	0.34	0.02	0.02	5	0.21	0.22
1.20	0.93	0.79	0.47	0.20	0.35	0.72	1.29	0.72	0.28	0.31	0.24	7	0.31	0.32
1.16	0.96	0.68	0.32	0.10	0.44	0.93	1.57	0.63	0.22	0.64	0.19	6	0.34	0.34
1.50	0.97	0.79	0.19	0.02	0.15	0.75	0.69	1.76	0.10	0.02	0.08	9	0.40	0.34
1.37	0.76	1.03	0.15	0.14	0.40	0.87	0.80	1.18	0.25	0.16	0.03	8	0.29	0.29
1.41	1.12	0.79	0.43	0.22	0.50	0.92	0.72	0.68	0.34	0.28	0.09	0	0.39	0.38
1.23	1.13	1.11	0.12	0.33	0.35	0.66	1.16	0.92	0.19	0.17	0.01	5	0.27	0.25
1.44	1.01	0.78	0.24	0.15	0.14	0.87	1.07	0.81	0.33	0.04	0.06	7	0.34	0.32
1.28	1.12	0.71	0.06	0.06	0.22	1.54	1.15	0.69	0.64	0.12	0.04	6	0.33	0.33
1.19	1.08	0.78	0.01	0.24	0.38	0.81	0.67	1.28	0.39	0.00	0.09	4	0.33	0.31
1.23	1.22	0.86	0.20	0.18	0.30	1.16	1.02	0.67	0.32	0.37	0.04	6	0.28	0.29
1.42	0.69	1.04	0.44	0.02	0.44	0.66	0.88	1.07	0.22	0.17	0.04	8	0.28	0.29
1.37	1.02	0.81	0.27	0.20	0.25	0.91	1.07	0.73	0.29	0.03	0.18	7	0.33	0.31
1.44	0.68	0.91	0.11	0.04	0.39	0.73	0.88	1.59	0.02	0.29	0.41	8	0.33	0.34
1.20	0.79	0.98	0.23	0.21	0.41	1.26	0.96	0.71	0.25	0.45	0.18	6	0.34	0.30
0.99	1.05	0.67	0.04	0.35	0.13	0.99	0.96	1.06	0.53	0.07	0.18	9	0.35	0.35
1.20	0.71	0.97	0.23	0.17	0.40	0.75	0.73	1.94	0.25	0.21	0.24	8	0.30	0.32
1.32	0.98	1.03	0.08	0.00	0.33	0.79	0.82	1.22	0.14	0.03	0.06	0	0.33	0.34

Table 6.6 Examples of Training data and Output of The ANN for the second case

(Faults at Bus-8)

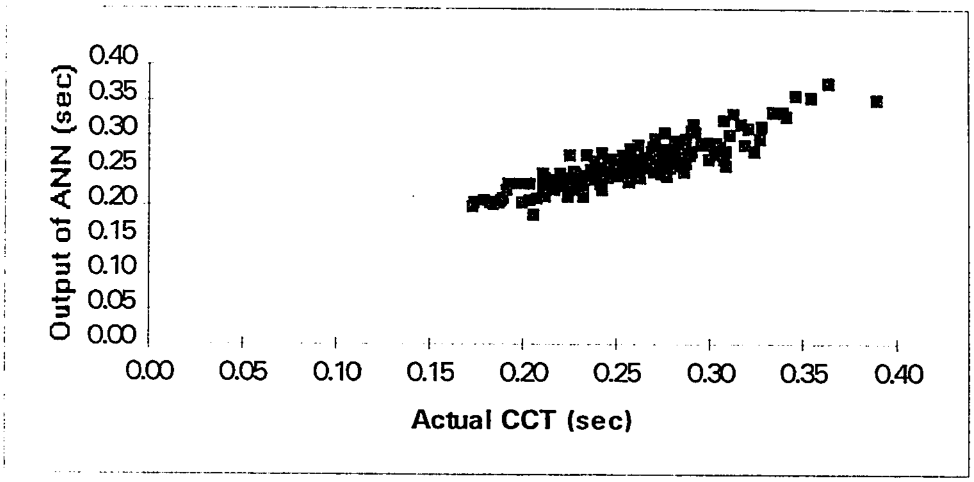

Figure 6.8 Output of The ANN for the second case for Faults at Bus-9

P_g (1)	P_g (2)	P_g(3)	Q_g (1)	Q_g (2)	Q_g (3)	R_a	R_b	R_c	L_a	L_b	L_c	L_{trip}	Actual CCT	ANN output
0.98	1.18	0.77	0.14	0.13	0.48	1.69	0.77	0.69	0.18	0.20	0.14	4	0.27	0.29
1.41	0.95	0.74	0.24	0.50	0.21	1.15	0.74	0.72	0.31	0.12	0.27	9	0.25	0.25
1.41	0.86	0.73	0.09	0.30	0.32	0.71	1.57	0.92	0.16	0.55	0.22	0	0.31	0.32
0.66	0.87	0.90	0.07	0.46	0.46	0.69	0.90	1.70	0.22	0.56	0.29	4	0.23	0.24
1.44	1.07	0.94	0.16	0.09	0.18	0.85	1.46	0.67	0.16	0.08	0.03	7	0.23	0.23
0.91	1.07	0.97	0.01	0.19	0.49	0.81	0.85	1.05	0.02	0.01	0.80	5	0.23	0.25
1.31	1.03	0.85	0.10	0.06	0.30	0.99	1.45	0.69	0.06	0.39	0.10	6	0.27	0.26
1.49	0.98	0.68	0.32	0.15	0.23	1.58	0.68	0.77	0.31	0.04	0.25	7	0.29	0.31
1.13	1.13	0.98	0.04	0.35	0.39	0.76	1.65	0.72	0.10	0.23	0.21	5	0.23	0.24
1.08	0.83	0.68	0.37	0.07	0.27	1.28	1.16	0.68	0.32	0.80	0.16	7	0.30	0.29
1.23	1.20	0.68	0.34	0.25	0.15	0.68	1.11	0.75	0.10	0.15	0.13	9	0.26	0.24
1.32	0.75	0.82	0.30	0.20	0.20	0.85	0.74	1.18	0.27	0.05	0.48	9	0.23	0.24
0.92	0.72	0.89	0.03	0.21	0.50	0.85	1.26	1.12	0.26	0.37	0.52	8	0.22	0.24
0.89	1.22	0.87	0.02	0.12	0.42	1.28	0.81	0.84	0.06	0.11	0.18	4	0.26	0.25
1.48	0.87	0.70	0.02	0.08	0.03	0.76	1.41	1.23	0.03	0.06	0.19	7	0.28	0.26
1.23	0.74	1.09	0.05	0.07	0.45	0.75	1.88	0.81	0.17	0.19	0.05	8	0.20	0.20
1.43	1.12	0.67	0.38	0.19	0.42	1.02	0.62	0.88	0.44	0.21	0.05	0	0.39	0.35
1.04	0.89	0.73	0.03	0.17	0.45	0.83	0.87	1.10	0.34	0.04	0.27	4	0.30	0.27
1.20	1.10	0.82	0.33	0.05	0.42	0.96	0.74	0.81	0.58	0.12	0.04	0	0.28	0.28
1.25	0.87	0.92	0.26	0.08	0.37	1.03	1.08	0.70	0.16	0.68	0.09	6	0.25	0.26

Table 6.7 Examples of Training data and Output of The ANN for the second case

(Faults at Bus-9)

The previous figures and tables indicates that the outputs of the ANNs for the first case are more accurate in comparison with the outputs of the ANNs for the second case. The best results correspond to the ANNs trained for faults at Bus-9 for both cases.

	7	8	9
type-1	0.0192	0.0215	.0064
type-1/lines removed	0.0298	0.0255	0.0170

Table 6.8 RMS. of error of ANN outputs

Table 6.8 shows the RMS. values of the error, the difference between the ANNs outputs and the CCT values obtained by the EEAC method. This table indicates, as mentioned above, that the ANNs trained for faults at Bus-9 provides more accurate CCT estimate in comparison with other ANNs trained for faults at Buses 7, and 8. Also, it is clear that the RMS. values are larger for the second case in comparison with those of the first case. In general, it can be stated that the outputs of the ANNs match the CCTs obtained by the EEAC method with an acceptable level of accuracy.

CHAPTER VII

Conclusions and Recommended Future Work

This chapter presents the conclusions arising from the work summarized in the previous chapters and give suggestions for future research work.

7.1 General observations and conclusions

In this research, Artificial Neural Networks (ANNs) have been used to assess the Transient Stability of three-machine-nine-bus system through its Critical Fault Clearing time. The parameters to these ANNs consist of the generation and loading levels. None of these inputs require any transient computations. This feature is desirable for on-line Transient Stability Assessment purposes.

Training of ANNs was achieved using a combined production learning phase. In other words, training patterns were not limited to a given collection of training samples. This scheme eliminates the problem that an ANN may be influenced with the regions of attraction of a specific categories.

Increasing the size of an ANN is expected to enhance its ability to absorb the behavior of the given system. However, this technique can not guarantee neither full convergence nor convergence to an acceptable level of accuracy.

Researches, reported previously, show a tendency to impos retractions on the number of topologies and the operating conditions. For example, topologies were limited by allowing only one line to be out of service at the instant of fault [30]. Others allowed two lines to be out of service at the instant of fault (not more than one line at once) [39]. Load levels, in other previous works, were subject to restrictions on their power factor (pf) [40]. Others restricted the load variations with a common level at all sites [30]. In this work, all of these restrictions were avoided.

The results obtained in this research agree, generally, with those reported recently [30,39,40,41]. The results summarized in the previous chapter indicates that the ANNs performance is affected strongly with variations in the power system structure (lines removal). The CCTs obtained for faults at bus nine are, obviously, the best among other cases where fault occur at other locations.

7.2 Recommended Future work

The CCTs value obtained by the ANNs were not consistently accurate. Hence, it is recommended to impose realistic restrictions on the operating conditions variations. Such restrictions may include optimal dispatch polices. Optimal dispatch reduce the input's state space and it is expected to simplify the mapping of the input patterns to the CCT.

It is also recommended to use other types of ANNs, other than the multilayer backpropagation ANNs for estimating the CCT. Also, it is recommended to develop more effective ANNs' training technique.

References

[1] **Stewart E. Stanton**: 'Transient Stability Monitoring for Power Systems Using a Partial Energy Function', IEEE Transactions on Power Systems, Vol. 4, NO. 4, pp. 1389-1395 , 1989.

[2] **S.Y. Lee, H. D. Chiang, K. G. LEE** and **B. Y. Ku:** Parallel Power System Transient Stability Analysis on Hypercube Multiprocessors', IEEE Transactions on Power systems, Vol. 6, NO. 3, pp. 1337-43, August 1991

[3] **H. Shaaban** and **Lj. Grujic**: 'Transient Stability Analysis of Large-Scale Power Systems with Speed Governor via Vector Lyapunov Functions', IEE Proceedings, Vol. 132, Pt. D, No. 2, pp. 45-52, March 1985.

[4] **A.V. Machias** : 'Analysis of Transient Stability of a Multimachine Power System Using a Variable Gradient Lyapunov Function', IEE Proceedings, Vol. 133, Pt. C, No. 2, pp. 81-6, March 1986.

[5] **M. RIBBENS-PAVELLA.**, and **F. J. EVANS** : 'Direct Methods for Studying Dynamics of Large-scale Electric Power Systems - A Survey', Automatica, Vol. 21, No. 1, pp. 1-21, 1985.

[6] **A. M. Eskicioglu**, and **O. Sevaioglu** : 'Feasibility of Lyapunov Functions for Power System Transient Stability Analysis by the Controlling UEP Method', IEE Proceedings-C, Vol. 2, pp. 152-6, March 1992.

[7] **P. Rastgoufard** and **R. A. Sxhlueter**.: 'Multi-Machine Equal Area Based Power System Transient Stability Measure', IEEE Transactions on Power Systems, Vol. 3, NO. 1, pp. 188-96, February 1988.

[8] **Y. Xue, Th. Van Cutsem**. and **M. Ribbens-Pavella**.: 'A simple Direct Method for Fast Transient Stability Assessment of Large Power Systems', IEEE Transactions on Power Systems, Vol. 3, NO. 2, pp. 400-11, May 1988.

[9] **Y. Xue, Th. Van Cutsem**. and **M. Ribbens-Pavella**.: 'Extended Equal Area Criterion Justifications, Generalizations Applications', IEEE Transactions on Power Systems, Vol. 4, NO. 1, pp. 44-52, February 1989.

[10] **B. Heilbronn, E. Euxibie, J.F. Lesigne, M. Pawella, P. Rousseaux, L. Wehenkel, R. Belhomme and Y. Xue**: 'Extended Equal Area Criterion Revisited', IEEE Transactions on Power Systems, Vol. 7, NO. 3, pp. 1012-1022, August 1992.

[11] **Y. Dong**, and **H. R. Pota**, : 'Transient Stability Margin Prediction Using Equal-Area Criterion ', IEE Proceedings-C, Vol. 140, No. 2, pp. 96-104, March 1993.

[12] **A. A. Fouad, V. Vittal** and **S. Rajagopal** : 'Direct Transient Stability Analysis Using Energy Functions Application to Large Power Networks', IEEE Transactions on Power Systems, Vol. PWRS-2, NO. 1, pp. 37-44 , February 1987.

[13] **V. Vittal, S. Rajagopal, M. A. El-Kady** and **E. Vaahedi** : 'Transient Stability Analysis of Stressed Power Systems Using the Energy Function Method', IEEE Transactions on Power Systems, Vol. 3, NO. 1, pp. 239-244, February 1988.

[14] **M. M. Abu-Elnaga, M. A. El-Kady** and **R. D. Findlay**: 'Sparse Formulation of the Transient Energy Function Method for Applications to Large-Scale Power Systems', IEEE Transactions on Power Systems, Vol. 3, NO. 4, pp. 1648-54, November 1988.

[15] **V. Vittal, N. Bhatia, A. A. Fouad, G. A. Maria,** and **H. M. Zein El-Din**.: 'Incorporation of Nonlinear Load Models in The Transient Energy Function Method', IEEE Transactions on Power Systems, Vol. 4, NO. 3, pp. 1031-35, August 1989.

[16] **T. Athay, R. Podmore, S. Virmani**: 'A Practical Method for the Direct Analysis of Transient Stability', IEEE Transactions on Power Apparatus and Systems, Vol. PAS.-98, NO. 2, pp. 573-84, March/April 1979.

[17] **V. Vittal, G. M. Prabhu,** and **Swee Lian Lim**.: 'A Parallel Computer Implementation of Power System Transient Stability Assessment Using The Transient Energy Function Method', IEEE Transactions on Power Systems, Vol. 6, NO. 1, pp. 167-73, February 1991.

[18] **A.A. FOUAD** and **V. VITTAL** , Power System Transient Stability Analysis Using the Transient Energy Function Method, Prentice Hall, 1992.

[19] **F. A. RAHIMI, K. L. LEE, J. N. WRUBEL,**. and **M. G. AUBY,**.: 'Evaluation of the Transient Energy Function Method for On-line Dynamic Security Analysis', IEEE Transactions on Power Systems, Vol. 8, NO. 2, pp. 497-507, May 1993.

[20] **C. L. Gupta**: 'Transient Security assessment of power systems by Pattern Recognition and Lyapunov Direct Method', Purdue University, TR-EE 76-35, August, 1976.

[21] **M. Sato,** 'A Pattern Recognition Approach for Transient Security Assessment', Purdue University, TR-EE 79-9, December, 1978.

[22] **R. Belhomme, Th. Van Cutsem, M. Ribbens-Pavella,** 'A novel Pattern Recognition Approach to Transient Stability Assessment of Power Systems', IFAC World Congress, Munich, July 27-31, 1987

[23] **P. Schnupp, C. T., Nguyen Huu** and **L. W. Bernhard**, Expert System Lab Course, Springer-Verlag Berlin Heidelerg, 1989.

[24] **Tharam S. Dillon** and **Michael A. Laughton**, Expert System Applications in Power Systems, Prentice Hall, 1990.

[25] **L. Wehenkel, Th. Van Cutsem** and **M. Ribbens-Pavella** : 'An Artificial Intelligence Framework for on-line Transient Stability Assessment of Power Systems', IEEE Transactions on Power Systems, Vol. 4, NO. 2, pp. 789-800, May 1989.

[26] **A. A. Fouad, J. A. Davis** and **S. Venkataraman** : 'An Expert System for Security Trend Analysis of A Stability-Limited Power System', IEEE Transactions on Power Systems, Vol. 6, NO. 3, pp. 1077-84, August 1991.

[27] **Shirai, G.** and **Tamura, Y. Etal** : 'Expert System for Power System Stabilization Based upon the Second Lyapunov Function', Proc. ESAPS, pp. 5.9-5.15.

[28] **D. B. Klapper, H. Tanaka, J. Yoshizawa, K. A. Wirgau, Yo. Akimoto** and **W. W. Price** : 'Transient Stability Expert System', IEEE Transactions on Power Systems, Vol. 4, NO. 1, pp. , February 1989.

[29] **Dan W. Patterson**, Introduction to Artificial Intelligence and Expert Systems, Prentice Hall I, 1990.

[30] **Dejan j. Sobajic and Yoh-Han Pao**: 'Artificial Neural-Net Based Dynamic Security Assessment for Electric Power Systems', IEEE Transactions on Power Systems, Vol. 4, NO. 1, pp. 220-28, February 1989.

[31] **Y. Xhang, G. P. Chen, O.P. Malik** and **G. S. Hope** 'An Artificial Neural Network Based Adaptive Power System Stabilizer', IEEE Transactions on Energy Conversion, Vol. 8, NO. 1, pp. 71-7, March 1993.

[32] **D. C. Park. M. A. El-Sharkawi, M. Aggoune, M.j. Damborg and R.J. Marksll**: 'Preliminary Results on Using Artificial Neural Networks for Security Assessment', IEEE Transactions on Power Systems, Vol. 6, NO. 2, pp. 890-896 , May 1991.

[33] **R. K. Hartana** and **G. G. Richards** 'Harmonic Source Monitoring and Identification Using Neural Networks', IEEE Transactions on Power Systems, Vol. 5, NO. 4, pp. 1098-104, November 1990.

[34] **Mo-yuen Chow** and **Robewt J. Thomas**: 'Neural Network Synchronous Machine Modeling', Proceeding of 1989 IEEE International Symposium on Circuit and Systems, Vol. 1, pp. 495-98, Portland, OR, May 8-11, 1989.

[35] **Sonja Ebron, David L. Lubkeman** and **Mark White**: 'A Neural Network Approach to the Detection of Incipient Faults on Power Distribution Feeders', IEEE Transactions on Power Delivery, Vol. 5, NO. 2, pp. 905-14, April 1990.

[36] **Samir Ahmed Zainaddin**: 'A Neural Network Approach for Load Flow Estimation and Var Allocation', MS. Thesis, King Fahd University of Petroleum and Minerals, pp. 37-40, June 1994.

[37] **YUAN-YIH HSU** and **CHAO-RONG CHEN**: 'Tuning of Power System Stabilizers Using an Artificial Neural Network', IEEE Transactions on Energy Conversion, Vol. 6, NO. 4, pp. 612-19, Dec. 1991

[38] **M. DJUKANOVIC, D. J. SOBAJIC** and **Y. H. PAO**: 'Neural net based determination of generator-shedding requirements in electric power systems', IEE Proceedings-c, Vol. 139, NO. 5, pp. 427-36, Sep. 1992.

[39] **E. Hobson** and **G. N. Allen** : 'Effectiveness of Artificial Neural Networks for First Swing Stability Determination of Practical Systems', IEEE Transactions on Power Systems, Vol. 9, NO. 2, pp. 1062-8, May 1994.

[40] **Masahide Nishiura, Yasuharu Ohasawa, Kenji Arai** and **Hiromasa Takeno:** 'Transient Stability Assessment Using Energy Function and Neural Network', Dept. of Electrical and Electronics Eng., Kobe University Rokkodaik, Nada 657 Kobe Japan, September 1994.

[41] **D. R. Marpaka, M. Bodruzzaman, S. S. Devgan, S. M. Aghili** and **S. Kari:** 'Neural Network Based Transient Stability Assessment of Electric Power Systems', Electric Power Systems Research 30 (1994) 251-256.

[42] **A.A. FOUAD** and **P. M. Anderson** , Power System Control and Stability, pp.38-44, The Iowa State University Press, AMES, Iowa, U.S.A.